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Geographically Weighted Regression to Explore Spatially Varying Relationships of Recreation Resource Impacts: A Case Study from Adirondack Park, New York, USA

Min-Kook Kim[a] and David Graefe[b]

[a] Department of Natural Resources and the Environment, Marshall University, Huntington, West Virginia
[b] Department of Recreation Management, Lock Haven University, Lock Haven, Pennsylvania

Please send correspondence to Min-Kook Kim, kimm@marshall.edu

Executive Summary

Empirical studies based on spatial explorations have played a critical role in understanding dynamics of recreation resource impact and recovery at multiple scales. However, little research has been done to examine spatially varying relationships between resource conditions and associated geospatial variables, especially using a predictive modeling approach. The primary purpose of this study was to explore spatially varying relationships of recreation resource impacts by using a geographically weighted regression (GWR) model. Specifically, the study was designed to compare the GWR with an ordinary least squares (OLS) multiple linear regression model to better understand localized spatial variations with roadside campsite conditions in Adirondack Park, NY, USA. Geospatial variables contained in the OLS model explained approximately 22% of the variance in campsite conditions (adjusted $R^2 = 0.220$, $p < 0.001$). Statistically significant predictors of the campsite condition at the global scale included site circumference, distance from water resource, distance from major road, distance from hosting forest road, and slope. Non-significant variables included site designation, distance from recreational trail, and elevation. The subsequent analysis using the GWR model resulted in adjusted R^2 values ranging from 0.198 to 0.271 (mean = 0.221). Roadside campsites located in the northern region of the park exhibited relatively higher R^2 values, and roadside campsites located in the southern region exhibited relatively lower R^2 values. All of the statistically significant global variables showed spatially varying relationships with the campsite condition. Additionally, elevation and site designation factors in the GWR model, which were non-significant variables at the global scale, suggested localized spatial variations with the campsite condition. Overall, the GWR model provided a more robust examination of campsite condition by accounting for localized spatial variations and by improving the model performance. This paper provides a discussion of the methodological and resource management implications of these findings.

Keywords

Recreation resource impact, spatial variation, spatially varying relationship, spatial modeling, geographically weighted regression

Introduction

Background and Objective

Identifying spatial patterns of recreation resource impact and recovery is essential in parks and protected areas (Hammitt et al., 2015). From the perspectives of public land management agencies, the information found and provided can be an indispensable factor in allocating their limited resources efficiently to satisfy a dual (or multiple) mission of the agencies. For this reason, the fields of recreation resource management and recreation ecology have constantly investigated spatial patterns of impact and recovery through diverse methods and approaches (Barros & Pickering, 2017; Cole & Monz, 2004; Kim et al., 2014; Monz et al., 2010; Ólafsdóttir & Runnström, 2013; Wimpey & Marion, 2011). The empirical studies based on spatial explorations are beneficial, and have played a critical role in: 1) discovering spatial pattern and distribution of impact/recovery, 2) identifying potential causes and effects of impact/recovery at a site level, and 3) evaluating relative effectiveness of management actions/strategies by verifying the attributes and degrees of resource impacts. However, little research has been done to examine spatially varying relationships between resource conditions and associated geospatial determinants, especially using a predictive modeling approach. Understanding spatially varying relationships or localized spatial variations is particularly important for a large spatial scale analysis because even the same variable can have a different level of local, regional, or global influence over resource conditions. Such information, which cannot be obtained in a linear model, must be provided to further support management efforts in parks and protected areas.

A previous study attempted to identify the potential relationships between the condition class in the roadside campsites in the Adirondack Park (AP) and associated geospatial characteristics of the campsites via an ordinary least squares (OLS) multiple linear regression model (Graefe & Kim, 2014). While the OLS model was useful for understanding the relationships among the variables at the global scale, one of the limitations was that it lacked the identification of local or regional variations of the geospatial variables contained in the model, especially in the context of spatial effects and relationships. Do the relationships between the campsite condition and the independent variables vary across the study region? In other words, are there any spatial dependence or spatial heterogeneity in the variables that influence the campsite condition in the AP? What are the potential local spatial relationships between the campsite condition and the associated variables? To answer these questions, a geographically weighted regression (GWR) model was proposed as a critical next step for research. Thus, the purpose of this study was to utilize a GWR model to identify spatially varying factors that influence the roadside campsite impacts in the park, and to compare the results between the OLS multiple linear regression and the GWR.

Literature Review

GWR Model

Traditional multivariate OLS regression in examining recreation resource impacts has limitations in dealing with spatial effects such as spatial dependence (often referred as to spatial autocorrelation, or second-order spatial effects) and spatial heterogeneity (often referred as to spatial non-stationary, first-order spatial effects, locality-specific, or spatial variability) (Fotheringham et al., 2002; Gao & Li, 2011; Jang & Kim, 2018; Kim & Nicholls, 2016; Matthews & Yang, 2012; Mennis & Jordan, 2005; Tenerelli et al., 2016; Xu et al., 2018). With this issue, the results of OLS models based on spatial data could produce biased estimations by yielding relatively larger residuals (Anselin, 1988). While both spatial dependence and spatial heterogeneity are intrinsically related, spatial dependence frequently means that there will be more similarities or similar characteristics in close proximity based on Tobler's First Law of Geography (Tobler, 1970), and spatial heterogeneity often implies that the relationships between independent and dependent variables are not constant across space (Fotheringham et al., 2002; Tu & Xia, 2008).

A premier advantage of using a GWS model is to verify local and regional variations in relationships among variables. Specifically, spatial heterogeneity can be captured in a GWR model by altering the local form of linear regression equations in each location of data (Brunsdon et al., 1996; ESRI, n.d.; Lee & Schuett, 2014; Tenerelli et al., 2016; Zhang et al., 2011). Second, a GWR model reduces error terms (often referred to as autocorrelation in residuals) compared to a conventional OLS model. Subsequently, the model built could provide improved model performance (Gilbert & Chakraborty, 2011; Kim & Nicholls, 2016). Third, GWR can help visualize spatial variations such as local R^2 values and parameter estimates (Gilbert & Chakraborty, 2011; Kim & Nicholls, 2016; Lee et al., 2017; Wang et al., 2020). Since a GWR model can generate a local coefficient for each observation, it could be utilized effectively to visualize spatial variations among variables in the model (Fotheringham et al., 2002; Kim & Nicholls, 2016). In sum, a GWR model is considered to be a more robust and reasonable tool for capturing local variations between independent and dependent variables (Hu et al. 2015; Kim & Nicholls, 2016). A GWR model can be specified as follows:

$$y_i = \beta_{i0} + \beta_{i1} x_{1i} + \beta_{i2} x_{2i} + \ldots + \beta_{in} x_{ni} + \varepsilon i,$$

where y_i is dependent variable, β_{i0} is intercept, β_i is coefficient, and ε_i is errors at location (i). Unlike an OLS where coefficients are spatially uniform across space, local intercepts (β_{i0}) and local coefficients (β_i) are determined by the location (i) in the GWR model (Fotheringham et al., 2002; Kuo et al., 2017). Weighting function, which is based on distance-decay, is used to estimate the regression parameters in every location of the data point, and it is determined by kernel types (fixed or adaptive) and bandwidth methods (Fotheringham et al., 2002; Jivraj et al., 2013; Lee & Schuett, 2014). When fixed, the distance to count nearby neighbors will be fixed to estimate the regression parameters in each data point. Under the adaptive option, the distance will vary by the characteristic of spatial data either to calculate an optimal number of neighbors or to count a specific number of neighbors given in a computation (ESRI, n.d.). In general, a larger bandwidth, which considers more neighbors, produces a smoother regression result closer to an OLS (could be an over-smoothed model), and a smaller bandwidth produces a less smooth regression result and much local variation (could be an under-smoothed model) (Jivraj et al., 2013; Kim & Nicholls, 2016).

A growing body of research has shown the utility and feasibility of the GWR modeling approach. Kim and Nicholls (2016) explored the utility of GWR models in analyzing the degrees of equity inherent in the distribution of access to public open spaces in the Detroit Metropolitan Area. Their study provided the notable advantages of the GWR models by showing significantly improved statistical results: higher R^2 values, lower Moran's I of standardized residuals, and lower corrected Akaike Information Criterion (AIC_c) in the GWR models. Lee and Schuett (2014) examined the utility of a GWR model in verifying the relationship between recreational demand (park visitation) and its associated sociodemographic and economic factors, demonstrating how spatially varying relationships could be revealed statewide (Texas). Lee et al. (2017) utilized a GWR at a larger spatial scale, as a promising tool for detecting spatial heterogeneity and reducing spatial autocorrelation in the residuals, to investigate the spatially varying relationships between physical inactivity and physical environments as well as socio-economic variables at the county level in the U.S. Xu et al. (2018) examined the spatial variation of urban green space equity and its relationship with socioeconomic variables in the region of Munich, Southern Germany, using several spatial analyses and statistics that include Gini coefficient, GWR, and dynamic scenario modeling approaches. Results showed that the variables are not always significantly related to each other over space, indicating greater spatial heterogeneity. Nilsson (2014) also examined spatially varying relationships between housing prices and proximity to preserved open space amenities and waterscapes in Sweden, suggesting spatial heterogeneity between the developed and undeveloped areas. Tenerelli et al. (2016) attempted to investigate how the actual provision of cultural services is spatially distributed. As a primary method, a geographically weighted poisson regression was used to identify spatially varying relations between the photo count (geotagged images from Flickr) and the landscape variables (landscape feature and accessibility of facilities) in a mountain landscape. Rasch et al. (2018) utilized GWR to examine spatially varying relationships between visitation level of overnight recreation site and presence of oil/gas well at 27 national forests in the U.S. Their study discovered that the sites within five kilometers of oil/gas wells had less visitation in the western states excluding California, but no significant effect on visitation in the eastern regions. These studies have focused on the identification of spatial distributions, spatial interactions, and spatial relationships among variables associated with demand and supply. Also, studies often tend to show distributional equity or inequity by identifying phenomena that have not been revealed so far, or by identifying local and regional trends spatially. The advantage of such studies is that information generated can be used directly by the agencies to support "data-driven" or "data-informed" decision-making processes. Moreover, a series of studies in tourism-related fields utilized GWR in their predictive models. Such studies have utilized hedonic price models based on GWR in examining hotel room prices (Soler & Gemar, 2018; Kim, Jang, Kang et al., 2020) and in exploring housing values close to beach (Kim, Yoon, Yang et al., 2020). Also, studies have focused on identifying spatially varying relationships between tourism destinations and food safety violations (Lee et al., 2019), between clusters of tourism industry and Airbnb performance (Lee et al., 2020), between density of Airbnb and property/crime index (Xu et al., 2019), and between intersectional social categories (e.g., house value, income, poverty) and food store access (Jang & Kim, 2018).

Methodologically, the majority of the studies showed the following sequences: 1) utilize various parametric and non-parametric statistics that try to identify relationships among variables (as a preliminary statistical analysis), 2) examine the utility of GWR models by comparing the statistical outcomes from OLS or other linear models, 3) verify spatial heterogeneity by identifying statistically significant local variables, 4) visualize the spatial heterogeneity and spatial dependence discovered, and 5) report better or improved statistical outcomes (e.g., higher R^2 values, lower AIC_c, lower condition numbers) over other modeling approaches. It is remarkable that many studies using the GWR approach have produced significant improvements of model performance over OLS or other linear models (Bascuñán & Quezada, 2016; Ge et al., 2017; Jang & Kim, 2018; Javi et al., 2014; Jivraj et al., 2013; Kim, Jang, Kang, et al., 2020; Kim & Nicholls, 2016; Kim, Yoon, Yang, et al., 2020; Lee et al., 2017; Lee et al., 2019; Lee et al., 2020; Lee & Schuett, 2014; Nilsson, 2014; Rasch et al., 2018; Tenerelli et al., 2016; Wang et al., 2020).

Interestingly, Matthews and Yang (2012) addressed the importance of developing a way to present GWR results, suggesting a GIS mapping approach based on local *t*-value and isolines to display significant and non-significant areas visually at a 95% confidence level. Kuo et al. (2017) calculated pseudo *t*-values to confirm statistically significant local coefficients in each variable and displayed positively and negatively significant areas in the GWR model. Javi et al. (2014) adopted various confidence levels (90%, 95%, and 99%) to visualize the different levels of significance in their GWR model between land use/cover changes and groundwater resources. Similarly, a few studies have utilized local *t*-values to verify statistically significant local coefficients and to display local variations visually (Bascuñán & Quezada, 2016; Fotheringham et al., 2013; Ge et al., 2017; Ngui & Caron, 2012; Rasch et al., 2018; Tu & Xia, 2008). Additionally, several studies, including Kim and Nicholls (2016), used a unique approach by generating a classification table to calculate the relative influences of local coefficients and local R^2 values compared to the estimates from other models (Kim, Jang, Kang et al., 2020; Kim & Nicholls, 2016; Kim, Yoon, Yang et al., 2020; Lee et al., 2019). Such studies are useful for presenting the outcomes of the GWR models, demonstrating relative success or performance improvement of the models, and improving methods for presenting spatially varying results.

Methods

Study Area Description

The AP, which comprises approximately 61 townships in an area of 19,700 km^2 (Glennon & Porter, 2005; McClain & Porter, 2000), is composed of interspersed public and private lands located in upstate New York (Graefe & Kim, 2014; Larkin & Beier; 2014). The region has a unique mountainous landscape with elevations ranging from 30 to 1,600 m (Glennon et al., 2015; McNeil et al., 2006), while dominant vegetation is a mixture of boreal and north hardwood forest (Glennon & Kretser, 2013). A detailed description of the characteristics of the management and camping opportunities in the AP can be found in the previous study. Given that the AP is one of the biologically diverse protected areas in the northeastern U.S., various aspects of natural resources have been studied: 1) human-induced impacts on wildlife communities (Glennon &

Kretser, 2013; Glennon et al., 2015; Glennon & Porter, 2005), 2) habitat analysis using remote sensing data (McClain & Porter, 2000), 3) forest disturbance analysis by GIS models (McNeil et al., 2006), and 4) wilderness perceptions among different user groups (Larkin & Beier, 2014).

Variables Used

Table 1 explains the dependent and independent variables used in the GWR model. To maintain consistency with the original OLS model, the same the dependent and independent variables were utilized. A total of 469 primitive roadside campsites were assessed, and a five-point condition class variable served as the dependent variable (class 1: 93, class 2: 111, class 3: 163, class 4: 92, class 5: 10) (Figure 1, left).

Table 1
Dependent and Independent Variables Used

Name	Data description
Condition Class	Five-scale condition class assessment data (1-5) covering the Adirondack Park Forest Preserve (a total of 469 campsites), the environmental condition of each campsite in relation to levels of soil compaction and vegetation health*
Campsite designation	A measure of whether or not a roadside campsite was officially designated (0 or 1)*
Distance from hosting F.P. road	An estimated distance from the center of a roadside campsite to its hosting road (unit: meter)*
Campsite circumference	A rough estimate of the size of each roadside campsite (unit: meter)*
Distance from major road	An estimated distance from the nearest major road calculated by the proximity tool (unit: meter)**
Distance from water resource	An estimated distance from the nearest water resource (e.g., lakes, ponds, streams, and rivers) calculated by the proximity tool (unit: meter)**
Distance from recreational trail	An estimated distance from the nearest recreational trail calculated by the proximity tool (unit: meter)**
Elevation	An estimated elevation calculated and extracted by spatial analysis tool (unit: meter)**
Slope	An estimated slope calculated and extracted by spatial analysis tool (unit: degree)**

* (Graefe et al., 2010).
** (Shared Adirondack Park Geographic Information Database, CD-ROM, ver. 1.0).

Data Analysis

All analyses were carried out using ESRI ArcMap (version 10.2) as well as Spatial Statistics Extension, and GWR (version 4.0, https://sgsup.asu.edu/sparc/gwr4) was used as a supplementary tool to test the statistical outcomes from the several combinations of different kernel types and bandwidth methods.

As a preliminary process, a global Moran's I of each variable was calculated to measure the degrees of spatial dependency, either clustered or dispersed relationship, in the roadside campsite data. This was done primarily to inspect the spatial distribution of each variable. The OLS model was first computed. Then, the GWR model was computed to explore spatial variations between the dependent variable and the independent variables. After many trials and errors regarding the kernel types and bandwidth methods, the Gaussian kernel type with a fixed distance, so-called fixed weighting (Tenerelli et al., 2016), and the AIC_c that finds an optimal distance or number of neighbors were eventually applied in the computation. Statistical estimates (local R^2 values, local coefficients, and local t-value) from the GWR model were calculated to compare with the OLS statistical estimates and to verify spatial variations at the local scale. The statistical estimates were also mapped further to investigate spatially varying relationships among variables in the region. Also, Moran's I of standardized residuals were compared between the OLS and the GWR models to check the improvement of the model fit.

Results

Results of Global Moran's I

Results of the global Moran's I analysis showed spatially clustered relationships in all variables (Table 2). These spatially clustered relationships were mainly caused by the nature and characteristics of the data itself (unevenly structured point data). As shown in Figure 1 (left), some roadside campsites are clustered, or conversely, some are dispersed. These results, however, suggest that the roadside campsites are not uniformly distributed over the study region, indicating spatial dependence at the level of individual variable.

Table 2
Result of Global Moran's I

Variable	Moran's I	Z-score	Relationship suggested
Condition Class	0.239259	4.493343**	Spatially clustered
Designation	0.613456	11.471399***	Spatially clustered
Distance	0.335054	6.331788***	Spatially clustered
Circumference	0.193480	3.691162*	Spatially clustered
Distance-R	0.924434	30.932552***	Spatially clustered
Distance-W	0.509604	9.579659***	Spatially clustered
Distance-T	0.422608	8.088535***	Spatially clustered
Elevation	0.884268	29.650408***	Spatially clustered
Slope	0.473491	9.076481***	Spatially clustered

* $p < 0.0001$, ** $p < 0.00001$, *** $p < 0.000001$

Results of OLS Model

As identified in the previous study, the Joint F-statistic and Joint Wald statistic suggested that the OLS model was statistically significant (Joint F: 17.50, $p < 0.01$, Joint Wald: 186.47, $p < 0.01$). All Variance Inflation Factors (VIF) were below 7.5, indicating no redundancy among the independent variables. The Koenker (B.P.) statistic (8.15, $p = 0.42$) suggested that the relationships modeled were consistent, regardless of non-stationarity or heteroskedasticity, and the Jarque-Bera Statistic (5.83, $p = 0.054$) indicated that the residuals were normally distributed. AIC_c was 1294.681 in the OLS model. The independent variables contained in the OLS model explained approximately 22% of the variance in campsite conditions (adjusted $R^2 = 0.220$, $p < 0.01$). Statistically significant global variables of the campsite condition, in decreasing order of effect size based on the standardized coefficients, included site circumference, distance from water resource, distance from major road, distance from hosting forest road, and slope. Non-significant variables included site designation, distance from recreational trail, and elevation (Table 3).

Results of GWR Model

Table 4 shows the comparison results between the OLS and GWR models. The adjusted local R^2 values varied over the study region ranging from 0.198 to 0.271 (mean = 0.221), showing relatively higher R^2 values in the northern part and lower R^2 values in the southern part of the region (Figure 1, center). The standard residuals of the GWR model, which shows the differences between the predicted values and the observed values, also varied over the study region ranging from -2.656 to 2.689 (mean = -0.007). The red points indicate under-predicted roadside campsites while the blue points show over-predicted roadside campsites (Figure 1, right).

Table 3
Results of OLS Model

Variable	Coefficient	Std Error	*t*-statistics	Prob	Robust S.E.	Robust *t*	Robust Prob	VIF
Intercept	1.387186	0.383369	3.618414	0.000342*	0.382697	3.624760	0.000334*	
Designation	0.126012	0.100338	1.255876	0.209803	0.103581	1.216557	0.224399	1.133033
Distance (hosting road)	0.001618	0.000382	4.240332	0.000031*	0.000351	4.614204	0.000007*	1.115636
Circumference	0.005339	0.001004	5.319859	0.000000*	0.001063	5.023668	0.000001*	1.114125
Distance-R (major road)	-0.000055	0.000016	-3.427357	0.000678*	0.000016	-3.497025	0.000530*	1.790202
Distance-W (water)	-0.000975	0.000188	-5.184789	0.000001*	0.000173	-5.646134	0.000000*	1.060260
Distance-T (trail)	0.000021	0.000034	0.623953	0.532969	0.000026	0.823268	0.410770	1.173178
Elevation	0.000793	0.000629	1.261194	0.207883	0.000620	1.278602	0.201688	1.905350
Slope	0.049871	0.015166	3.288374	0.001099*	0.012474	3.997854	0.000082*	1.161302

N = 469
$R^2 = 0.233362$, Adjusted $R^2 = 0.220029$
$AIC_c = 1294.681473$
Joint F: 17.50 ($p < 0.01$)
Joint Wald: 186.47, ($p < 0.01$)
Koenker (BP) statistic = 8.15 ($p = 0.42$)
Jarque-Bera Statistic = 5.83 ($p = 0.054$)
* $p < 0.01$

Figure 1
Spatial Distribution of Condition Class (left), Local R^2 Values (center), and Standard Residuals (right) of GWR

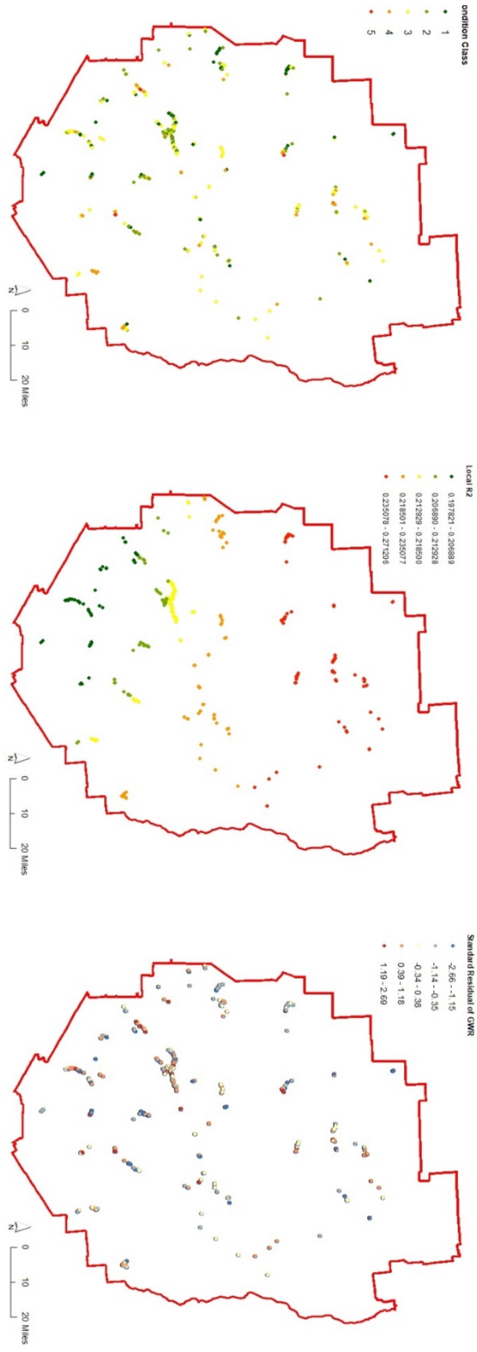


Table 4

Comparison Results between OLS and GWR

Variable	OLS Coefficient	GWR Coefficients				
		Mean	Minimum	Maximum	Range	Standard Deviation
Intercept	1.387186	1.450329	0.813215	1.998159	1.184945	0.234053
Designation	0.126012	0.086371	0.013918	0.252312	0.238394	0.056888
Distance	0.001618	0.001533	0.00146	0.001603	0.000143	0.000029
Circumference	0.005339	0.005191	0.004582	0.006055	0.001473	0.000331
Distance-R	-0.000055	-0.000052	-0.000065	-0.000045	0.00002	0.000004
Distance-W	-0.000975	-0.00098	-0.00108	-0.000894	0.000186	0.000035
Distance-T	0.000021	0.000025	0.000006	0.000037	0.000031	0.000007
Elevation	0.000793	0.00076	-0.000075	0.001602	0.001677	0.000346
Slope	0.049871	0.049482	0.036018	0.05851	0.022493	0.004639
Adjusted R^2	0.220029	0.221319	0.197821	0.271206	0.073384	0.017097
Condition No.	-	27.746465	24.80561	29.997383	5.191773	1.035746

$N = 469$
AIC_c (OLS) = 1294.681473, AIC_c (GWR) = 1290.896863
Neighbor = 105552.443208
Kernel type: fixed
Bandwidth method: AIC_c
OLS: Moran's I = 0.114422, z-score = 2.170469, $p = 0.029971$
GWR: Moran's I = 0.108815, z-score = 2.066168, $p = 0.038813$

The condition number, or condition index (Kim & Nicholls; 2016), helps diagnose multicollinearity (Hu, 2009; Lee & Schuett, 2014; Siordia et al., 2012). In general, condition numbers between 5 and 10 suggest weak dependence, and numbers over 30 suggest moderate or stronger dependence among the independent variables (Charlton & Fotheringham, 2009; Yang et al., 2013). Thus, if the condition numbers are greater than 30, unreliable coefficient estimates could be produced due to the local collinearity (ESRI, n.d.; Lee et al., 2017; Siordia et al., 2012; Yang et al., 2013). All condition numbers in the GWR model were below 30 (mean = 27.746), indicating no major issue related to local collinearity among the independent variables. The GWR model showed a small improvement in model performance compared to the OLS model. The adjusted R^2 value was increased from 0.220 to 0.228, and the AIC_c was decreased from 1294.681 to 1290.897. AIC_c is useful to compare model differences as well as model performance (Bozdogan, 1987; Kim & Nicholls, 2016; Matthews & Yang, 2012) and it is typically regarded the lower AIC_c and the higher R^2 value, the better (Gilbert & Chakraborty, 2011; Lee & Schuett, 2014; Tenerelli et al., 2016). Additionally, the Moran's I of standardized residuals was improved from 0.114 in the OLS model (z-score: 2.170, p = 0.030) to 0.109 in the GWR model (z-score: 2.066, p = 0.040). Both models had positive Moran's I, indicating spatial autocorrelation (spatially clustered), but the GWR model improved the model performance by reducing the spatial dependence in the residuals.

Approximately 37.53% of the roadside campsites in the GWR model shows higher local R^2 values than the original R^2 value in the OLS (Table 5). The variance of the roadside campsite conditions, especially in the northern region, was better explained by the GWR model, and the variance of the roadside campsite conditions in the southern region was less explained by the GWR model. All of the statistically significant global variables showed local spatial variations to a certain extent, based on spatial heterogeneity or local t-value at a 95% confidence level. Statistically non-significant global variables that exhibited local spatial variation were site designation and elevation. Statistically non-significant global variable that exhibited no/little local spatial variation was the distance from the trails.

Table 5
Classification of Campsite Condition by Local Coefficient, Local R^2, and Local t-Values

	Number of Campsite ($N = 469$)				
	LC (positive) > 0 (%)	**LC (negative) < 0 (%)**	**LC > GC (%)**	**LC < GC (%)**	**Local *t*-value ($t > 1.96$ or $t < -1.96$)**
Designation	469 (100%)	0 (0%)	92 (19.62%)	377 (80.38%)	28 (5.97%)
Distance	469 (100%)	0 (0%)	0 (0%)	469 (100%)	469 (100%)
Circumference	469 (100%)	0 (0%)	117 (24.95%)	352 (75.05%)	469 (100%)
Distance-R	0 (0%)	469 (100%)	354 (75.48%)	115 (24.52%)	469 (100%)
Distance-W	0 (0%)	469 (100%)	164 (34.97%)	305 (65.03%)	469 (100%)
Distance-T	469 (100%)	0 (0%)	342 (72.92%)	127 (27.08%)	0 (0%)
Elevation	457 (97.44%)	12 (2.56%)	248 (52.88%)	221 (47.12%)	39 (8.32%)
Slope	469 (100%)	0 (0%)	275 (58.63%)	194 (41.37%)	469 (100%)
Adjusted R^2	Adjusted R^2 (OLS): 0.220029		GWR > OLS (%)	GWR < OLS (%)	
	Adjusted R^2 (GWR): 0.228019		176 (37.53%)	293 (62.47%)	

Note: LC: local coefficient by GWR, GC: global coefficient by OLS

Intercept

The coefficient of intercept in the OLS model was 1.387 (constant, $p < 0.01$), indicating positive relationships with the condition class over the study region. In the GWR model, the range of the intercept was between 0.813 and 1.998 (mean = 1.450), showing more positive associations in the southeastern region. The coefficient surface map generated indicates that the campsites located in the southeastern part of the region are more likely to have a higher condition class, and the campsites located in the northwestern part of the region are more likely to have a lower condition class (Figure 2a).

Site Designation

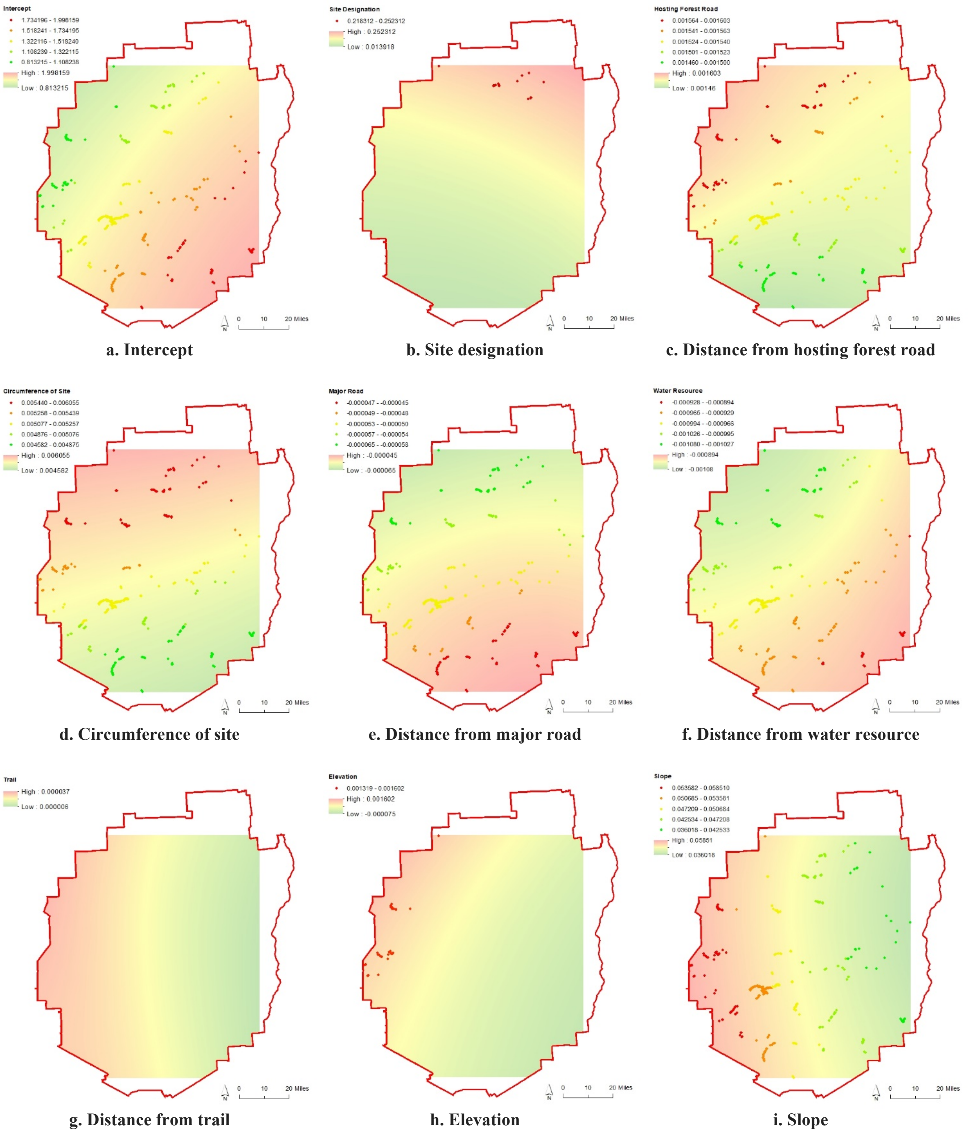
Site designation was a statistically non-significant variable in the OLS model, and the coefficient was 0.126 ($p > 0.01$). The local coefficient in the GWR model ranged from 0.014 to 0.252 (mean = 0.086), indicating positive relationships over the study region. While 92 (19.62%) of the roadside campsites showed greater local coefficients than the OLS coefficient, 337 (80.38%) had smaller local coefficients than the OLS coefficient. However, only 28 points in the northern part of the region were statistically significant at a 95% confidence level (local *t*-value > 1.96). The coefficient surface map generated indicates that the campsites officially designated in the northern part of the region are more likely to have a higher condition class (Figure 2b).

Distance from Hosting Forest Road

Distance from hosting forest road was a statistically significant variable in the OLS model, and the coefficient was 0.0016 ($p < 0.01$). The local coefficient in the GWR model ranged from 0.0015 to 0.0016 (mean = 0.0015), indicating positive relationships over the study region. All 469 roadside campsites had smaller local coefficients than the OLS coefficient and were statistically significant at a 95% confidence level (local *t*-value > 1.96). The coefficient surface map generated indicates that the campsites located away from the hosting forest road are more likely to have a higher condition class in the northwestern part of the region, and the campsites located away from the hosting forest road in the southern part of the region are more likely to have a lower condition class (Figure 2c).

Figure 2

Local Coefficient Surface Maps: Generated Under ArcMap 10.2 Spatial Analyst Extension (Interpolation Used: Spline, Spline Type: Regularized, Power: 0.1 [default], Number of Points: 12 [default]), Statistically Significant Points Displayed Only in Each Map.



a. Intercept
b. Site designation
c. Distance from hosting forest road
d. Circumference of site
e. Distance from major road
f. Distance from water resource
g. Distance from trail
h. Elevation
i. Slope

Circumference of Site

Circumference of site was a statistically significant variable in the OLS model, and the coefficient was 0.0053 ($p < 0.01$). The local coefficient in the GWR model ranged from 0.0046 to 0.0061 (mean = 0.0052), indicating positive relationships over the study region. While 117 (24.95%) of the roadside campsites showed greater local coefficients than the OLS coefficient, 352 (75.05%) had smaller local coefficients than the OLS coefficient. All 469 points were statistically significant at a 95% confidence level (local t-value > 1.96). The coefficient surface map generated indicates that the campsites larger in size are more likely to have a higher condition class in the northern part of the region, and the campsites larger in size in the southern part of the region are more likely to have a lower condition class (Figure 2d).

Distance from Major Road

Distance from major road was a statistically significant variable in the OLS model, and the coefficient was -0.00006 ($p < 0.01$). The local coefficient in the GWR model ranged from -0.00007 to -0.00005 (mean = -0.00005), indicating negative relationships over the study region. 354 (75.48%) of the roadside campsites showed greater local coefficients than the OLS coefficient, and 115 (24.52%) had smaller local coefficients than the OLS coefficient. All 469 points were statistically significant at a 95% confidence level (local t-value < -1.96). The coefficient surface map generated indicates that the campsites located away from the nearest major road are more likely to have a lower condition class in the northern part of the region, and the campsites located away from the nearest major road in the southern part of the region are more likely to have a higher condition class (Figure 2e).

Distance from Water Resource

Distance from water resource was a statistically significant variable in the OLS model, and the coefficient was -0.001 ($p < 0.01$). The local coefficient in the GWR model ranged from -0.001 to -0.0009 (mean = -0.001), indicating negative relationships over the study region. While 164 (34.97%) of the roadside campsites showed greater local coefficients than the OLS coefficient, 305 (65.03%) had smaller local coefficients than the OLS coefficient. All 469 points were statistically significant at a 95% confidence level (local t-value < -1.96). The coefficient surface map generated indicates that the campsites located away from the nearest water resource are more likely to have a lower condition class in the northwestern part of the region, and the campsites located away from the nearest water resource in the southeastern part of the region are more likely to have a higher condition class (Figure 2f).

Distance from Major Trails

Distance from major trails was a statistically non-significant variable in the OLS model, and the coefficient was 0.0002 ($p > 0.01$). The local coefficient in the GWR model ranged from 0.00006 to 0.0004 (mean = 0.0003), indicating positive relationships over the study region. While 342 (72.92%) of the roadside campsites showed greater local coefficients than the OLS coefficient, 127 (27.08%) had smaller local coefficients than the OLS coefficient. However, all 469 points were statistically non-significant at a 95% confidence level (local t-value < 1.96) (Figure 2g).

Elevation

Elevation was a statistically non-significant variable in the OLS model, and the coefficient was 0.0008 ($p > 0.01$). The local coefficient in the GWR model ranged from -0.0001 to 0.0016 (mean = 0.0008), indicating both positive and negative relationships simultaneously over the study region. While 248 (52.88%) of the roadside campsites showed greater local coefficients than the OLS coefficient, 221 (47.12%) had smaller local coefficients than the OLS coefficient. However, only 39 points in the western region were statistically significant at a 95% confidence level (local t-value > 1.96). The coefficient surface map generated indicates that the campsites located at higher elevations are more likely to have a higher condition class in the western region (Figure 2h).

Slope

Slope was a statistically significant variable in the OLS model, and the coefficient was 0.050 ($p < 0.01$). The local coefficient in the GWR model ranged from 0.036 to 0.059 (mean = 0.049), indicating positive relationships over the study region. While 275 (58.63%) of the roadside campsites showed greater local coefficients than the OLS coefficient, 194 (41.37%) had smaller local coefficients than the OLS coefficient. All 469 points were statistically significant at a 95% confidence level (local t-value > 1.96). The coefficient surface map generated indicates that the campsites located at steep slope areas are more likely to have a higher condition class in the western region, and the campsites located at steep slope areas in the eastern region are more likely to have a lower condition class (Figure 2i).

Discussion

The GWR model provided a more robust examination of the roadside campsite conditions by accounting for the localized spatial variations and by improving the model performance. Overall, the results of the GWR model showed more improved statistical outcomes, including higher R^2 values, lower AIC_c, and lower Moran's I of standardized residuals. The results also suggest that utilizing this new analysis approach, which considers local spatial variations and spatial dependence, is feasible in verifying the degrees of the roadside campsite condition class with the geospatial variables contained. The modeling approach used here shows advantages in verifying localized spatial variations. As identified in each local coefficient surface map generated, various local spatial variations, which could not be observed in the OLS model at the global scale, were elucidated by each variable and by each region. This result clearly shows that the variables contained in the model could not be applied uniformly in the process of recreation resource planning and management. Moreover, it is crucial to discover that the statistically non-significant variables at the global scale, such as site designation and elevation, have influences locally on higher condition classes (site designation: the northern region, elevation: the western region). In the future, to understand long-term characteristics of recreation resource changes, these variables could be continually utilized as essential variables in modeling that explain the condition class in the AP as well as other areas where similar environmental and recreational conditions exist. Also, since the local spatial variations found could be easily expressed as a form of the surface map, the utility of presenting spatial patterns and trends related to the dependent variable could be beneficial to managers and planners by increasing the understanding of the local variations. Presenting a prediction or changing situation, which could be generated by the model, would be helpful in monitoring natural resource conditions as a big picture of analysis outcome.

Kim and Nicholls (2016) suggested that a GWR model can broaden the scope of the research questions by allowing researchers to answer "where?" and "to what extent/how significantly?" Within the same context, Matthews and Yang (2012) mentioned "great richness in the results obtained" as a utility of a GWR model. Obviously, spatial data and predictive models, in general, have a number of advantages in terms of designing and widening research questions. Further, Levin (1980) argued, "There is no single natural scale at which ecological phenomena should be studied." Also, Wiens (1989) explained the concepts of grain (size of observation unit/angle) and extent (size of a study area) earlier. Both studies significantly influenced subsequent ecological study designs, and researchers often consider adopting a multiple spatial scale approach across space to identify relatively accurate or appropriate spatial scales in research. As a device to minimize uncertainty, the multiple spatial scale approach could be helpful to answer the questions associated with the cause and effect of an ecological phenomenon, and to discover the patterns and trends associated with resource use and its impact/recovery. With that in mind, we strongly believe that the GWR model and approach provides one more angle to observe changes in patterns and trends, by the utility and capability of investigating local and regional factors together across space. Such information capturing specific localized variables or locality-specific patterns, along with the utility by a global model, will offer a unique chance to observe ever-changing ecological conditions associated with visitor-induced impacts in parks and protected areas. Information gathered from a different angle and position, as well as repeated measures by other spatial statistics, could be beneficial to resource managers and planners in allocating their limited resources by considering management components, recreation opportunities, and ecological/biophysical conditions together. If this information is accumulated in a database, it would also be useful to answer specific questions that will emerge later in response to changes in ecological conditions. In that regard, this study could be expanded to any regions or units where the condition class assessment is widely used and accepted as the primary monitoring mechanism.

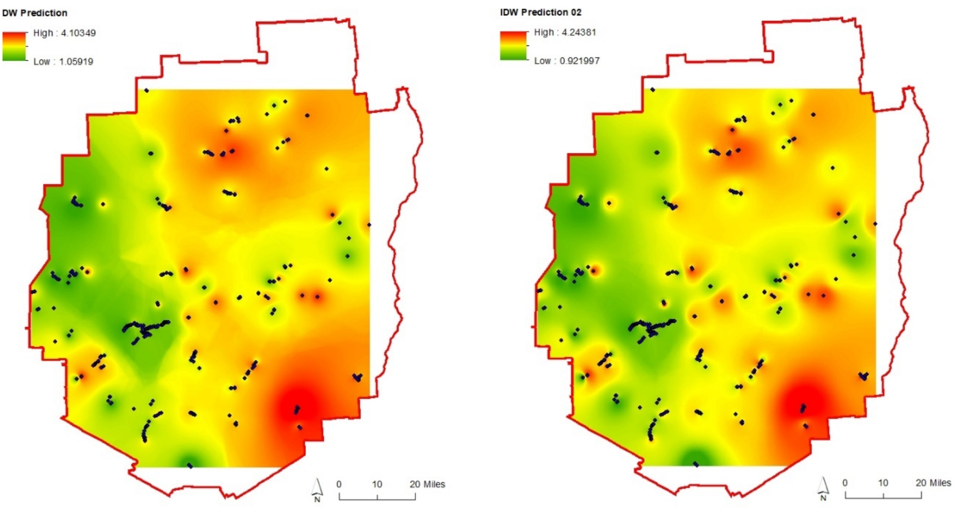
Management Implications

Cole (2001) discussed the significance of forecasting based on the near-past data to account for "alternative futures." Xu et al. (2018) addressed the importance of presenting potential scenarios associated with management efforts. A spatially explicit model (or model building) has an advantage of not only identifying the spatial variations, but also forecasting or predicting alternative scenarios for the near future. Although the scenarios are not precisely matched, it is imperative to open up more possibilities for what will likely occur in the near future and, at the same time, prepare a supporting system. This process would be the role of monitoring, providing an earlier warning of abnormal signs, if any.

As a way of enhancing such efforts, the prediction (y-hat) computed in the GWR model was additionally mapped to identify potential trends and patterns of the roadside campsite condition using a simple inverse-distance weighting (spatial interpolation) function (Figure 3). As an alternative method, a simple hot-spot or density mapping could be considered to show the likelihood (Ngui & Caron, 2012). While the two maps projected only reflected the eight independent variables, providing this type of information associated with the degrees of the condition class would be valuable in discovering overall patterns or trends. Based on the two different parameters, both maps show potentially higher condition classes in the southeastern and northern regions. Thus, management or monitoring could be prioritized in those areas to prevent further damages in resource conditions.

As identified, the AP is a six-million-acre parcel of interspersed public and private lands, which implies an extremely tough situation to discover uniformity in resource impact and recovery patterns. Under this circumstance, developing a spatially explicit model that identifies spatial dependence and spatial heterogeneity would be essential

Figure 3
Projection Maps: Generated Under ArcMap 10.2 Spatial Analyst Extension (interpolation used: inverse distance weighting, power: 2 (default), search radius class: variable, number of nearest input sample points: 50 (left), 100 (right)).



for recreation resource planning and management in the AP. The results of the model could be used as a management decision-making tool, to assist in understanding the consequences of the current and projected changing situations of the region, and to assist in visualizing through maps.

Research Limitations

It is difficult to understand why different patterns occur by each region and by each variable. For example, it is uncertain why the campsites located at higher elevations in the western region are more likely to have a higher condition class compared to other areas. It is also unclear why the campsites officially designated in the northern region are more likely to have a higher condition class compared to other areas. However, as specified, studies using spatial statistics and modeling often tend to focus more on phenomena that have not been revealed so far or local variations and trends rather than accurately answering the reasons behind the scenes. This is a typical outcome given the relatively large spatial scale of analysis. Thus, the questions above are, indeed, outside of the scope of this study, and more detailed and localized analyses might be required (Jivraj et al., 2013). This limitation also warrants that a holistic approach is required to better understand direct/indirect factors behind the different patterns in each variable or region via social science studies for use level/type and ecological analyses for resilience and resistance.

Another limitation would be data sources. As specified in the previous study, all proximity variables, slope, and elevation were extracted and calculated from the data included in the Shared Adirondack Park Geographic Information Database, CD-ROM (ver. 1.0), which was published in 2001. Thus, the analysis results may not reflect up-to-date situations regarding the variables extracted. Since the official website (https://

apa.ny.gov/gis/) is being constantly updated, new modeling in the future could utilize more recently updated data.

An advantage of the modeling approach is its flexibility, as several variables can be selected, tested, and contained in a model, especially using variables suggested from the previous studies, researcher's preferences, or local characteristics. However, this study only considered the original eight variables employed in the previous OLS model to maintain the consistency of the analysis. Thus, in the future, other potential biophysical variables (e.g., temperature, amount of rainfall, length of growing season, type of vegetation, type of soil, amount of sunlight/aspect, other ecological resilience and resistance characteristics) or use-related variables (e.g., use level, user behavior, type of activity, mode of travel) could be considered to improve the model fit. The characteristics of local areas or nearby towns (e.g., distances from amenities or living facilities) could be considered as well.

The outcome of a GWR model is highly influenced by the bandwidth selected (Gilbert & Chakraborty, 2011; Jivraj et al., 2013; Kim & Nicholls, 2016). For this reason, several combinations of different kernel types and bandwidth methods were tested before selecting the final set. The adaptive kernel produced the greater adjusted R^2 value (R^2 = 0.355), and the lower AIC_c (1279.458). However, the condition number was above 30 (below 40) in some data points, which may suggest a local collinearity issue. Therefore, the fixed kernel was eventually employed to minimize the issue. As smoothing techniques significantly influence the outcomes of the analysis, more considerations should be made in the future in selecting the kernel type and bandwidth methods, based on the spatial distribution of data.

It was possible to notice that there are some common aspects in reporting the statistical outcomes and measures among the GWR model studies. As an effort to structure the similarities in reporting the results of the GWR models, it is worth considering a standardized method on how to report the results, at least within the field of recreation resource management. The ODD (Overview, Design concepts, and Details) protocol is currently being used for reporting results in the field of an agent-based model or individual-based model (Grimm et al., 2010). Such a protocol would help reduce time and improve consistency in reporting results.

Conclusion

This study utilized the GWR model, an innovative approach that considers spatial effects such as spatial dependence and spatial non-stationary in a model, to examine the spatially varying relationships between the condition class of the roadside campsites and its associated variables in the AP. To the best of our knowledge, this study was the first attempt to understand the factors that influence a condition class under a certain recreational setting, both at global and local scales. The GWR model also enabled the determination of where the campsite condition class will be potentially higher or lower across the study region (i.e., potentially susceptible areas by the model result, clustered areas showing relatively higher condition classes, areas significantly influenced by the variables). Such information will provide a better understanding of local variations spatially and geographically, and another tool for efficiently prioritizing natural resource management needs. In sum, the utilities of GWR in recreation resource management include: 1) discovering spatially varying relationships or localized spatial variations of impact/recovery, 2) identifying potential causes and effects of impact/recovery at multiple spatial scales (locally, regionally, and globally), and 3) addressing alternative scenarios of natural resource change/condition based on predictive measures.

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